ReACT: Regime-Adaptive Contrastive Learning for EEG Representation Learning

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Abstract

Contrastive learning methods such as SimCLR (Simple Framework for Contrastive Learning) and SupCon (Supervised Contrastive Learning) are effective across many domains, but their behavior in noisy multivariate EEG time-series remains insufficiently understood. We show that contrastive performance is regime-dependent: instance-based learning is more robust in low-data settings, while supervised contrastive learning becomes more effective as data scale and class coverage increase. Motivated by this, we propose **ReACT** (Regime-Adaptive Contrastive Training), which dynamically balances instance-level and label-based supervision using training regime, subject identity, and representation consistency. Experiments on EEG motor-imagery benchmarks show that ReACT achieves more stable performance than SimCLR, SupCon, and fixed hybrid objectives, highlighting the importance of adaptive supervision in noisy high-variability time-series domains.

1. Introduction

Contrastive learning has become a major paradigm for representation learning, enabling neural networks to learn meaningful latent representations from unlabeled or weakly labeled data. Methods such as SimCLR (Chen et al., 2020) and Supervised Contrastive Learning (SupCon) (Khosla et al., 2020) have achieved strong performance across several domains by maximizing similarity between positive samples while separating negatives in the embedding space.

However, contrastive learning in multivariate time-series domains remains less understood. Physiological signals such as EEG are high-dimensional, noisy, temporally structured, and exhibit strong cross-subject variability. In addition, augmentations designed for vision tasks may distort temporal semantics, while supervised grouping can become unreliable when intra-class variability is high (Banville et al., 2021b; Mohammadi et al., 2023).

In this work, we investigate contrastive learning for EEG representation learning and identify a consistent regime-dependent phenomenon. Through experiments across multiple EEG benchmarks and varying training-data fractions, we observe that instance-based contrastive learning is generally more robust in low-data regimes, whereas supervised contrastive learning becomes increasingly effective as dataset scale increases. These findings suggest that the reliability of supervision varies across training regimes.

Existing methods rely on fixed positive-pair assumptions. SimCLR restricts positives to augmented views of the same instance, while SupCon treats all same-label samples as equally informative positives. In EEG data, however, samples sharing the same label may differ substantially across subjects, making supervised positives noisy. Fixed hybrid objectives similarly fail to adapt to changing supervision reliability. To address these limitations, we propose **ReACT** (Regime-Adaptive Contrastive Training), a contrastive learning framework that dynamically balances instance-level and label-based supervision. ReACT combines (i) regime-adaptive scheduling, (ii) subject-aware weighting, and (iii) representation-consistency weighting to reduce unreliable positive pairs and improve robustness under cross-subject variability. Our contributions are summarized as follows:

(1) We provide a systematic analysis of SimCLR and SupCon in EEG time-series learning, revealing a regime-dependent crossover between instance-level and supervised contrastive objectives. *(2)* We show that fixed supervised positive definitions become unreliable under strong intra-class and cross-subject variability. *(3)* We introduce ReACT, a regime-adaptive contrastive learning framework that dynamically weights positive pairs according to training regime, subject identity, and representation consistency. *(4)*We demonstrate that ReACT achieves more stable and consistent performance across datasets and training regimes compared to SimCLR, SupCon, and fixed hybrid objectives.

Overall, our findings highlight the importance of adaptive supervision for robust contrastive learning in noisy multivariate time-series domains.

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1.1. Related Work

Contrastive representation learning. Contrastive learning has become a major paradigm for self-supervised representation learning. Early work such as CPC (van den Oord et al., 2018) introduced predictive contrastive objectives, while later methods including SimCLR (Chen et al., 2020), MoCo (He et al., 2020), BYOL (Grill et al., 2020), SimSiam (Chen & He, 2021), and SupCon (Khosla et al., 2020) demonstrated strong representation learning performance using augmentations, momentum encoders, or supervised positives. However, these methods were primarily designed for image domains, where augmentations and class-level similarity are generally more stable than in physiological time-series data.

Self-supervised learning for time series and EEG. Recent studies have adapted contrastive learning to temporal data through temporal contrasting and neighborhood-based objectives (Eldele et al., 2021; Tonekaboni et al., 2021), as well as Transformer-based frameworks for multivariate time-series representation learning (Zerveas et al., 2021). In EEG, self-supervised learning has been explored for clinical EEG analysis and sleep staging (Banville et al., 2021a; Yang et al., 2023; Mohammadi Foumani et al., 2024), while broader surveys emphasize the importance of domain-specific augmentations and evaluation protocols (Hu et al., 2024; Del Pup et al., 2025). EEG decoding commonly relies on architectures such as EEGNet (Lawhern et al., 2018) and benchmark datasets including PhysioNet EEG Motor Movement/Imagery (Schalk et al., 2004) and BNCI datasets (Brunner et al., 2008; Tangermann et al., 2012). A major challenge across these studies is strong cross-subject variability, which can make fixed supervised positive definitions unreliable.

We study the regime-dependent behavior of SimCLR and SupCon across varying training-data fractions and introduce ReACT, which adaptively balances instance-level and supervised contrastive learning through regime-aware and reliability-based weighting.

2. Method

Let $\{x_i, y_i, s_i\}_{i=1}^{N}$ denote a multivariate EEG dataset, where $x_i \in \mathbb{R}^{C \times T}$ is a signal, y_i is the class label, and s_i is the subject identity. An encoder $f_\theta(\cdot)$ maps each sample to a normalized latent representation $z_i \in \mathbb{R}^d$.

Contrastive learning aims to maximize agreement between positive pairs while separating negatives in the embedding space. SimCLR (Chen et al., 2020) defines positives using augmented views of the same sample, whereas SupCon (Khosla et al., 2020) additionally treats same-label samples as positives. However, in noisy EEG settings with strong cross-subject variability, supervised positive pairs may become unreliable.

To address this, we propose **ReACT** (Regime-Adaptive Contrastive Training), which dynamically balances instance-level and label-based supervision according to training regime, subject identity, and representation consistency.

The ReACT objective is defined as (see Fig 2):

$$\mathcal{L}_{\text{ReACT}} = -\frac{1}{N} \sum_{i=1}^{N} \sum_{j \neq i} w_{ij} \log \frac{\exp(z_i^\top z_j / \tau)}{\sum_{k \neq i} \exp(z_i^\top z_k / \tau)} \tag{1}$$

where w_{ij} denotes the adaptive positive-pair weight and τ is the temperature parameter. The weighting function combines instance-level supervision, label supervision, subject-aware regularization, and representation reliability:

$$w_{ij} = (1-\alpha_t)\nVdash_{\text{aug}}(i,j) + \alpha_t \nVdash_{y_i=y_j} - \beta \nVdash_{s_i=s_j} + \gamma \text{sim}(z_i, z_j) \tag{2}$$

where $\nVdash_{\text{aug}}(i,j)$ denotes augmented-view positives, $\nVdash_{y_i=y_j}$ denotes same-label positives, and $\nVdash_{s_i=s_j}$ penalizes same-subject pairs. The similarity term

$$\text{sim}(z_i, z_j) = \frac{z_i^\top z_j + 1}{2} \tag{3}$$

assigns higher weights to more reliable pairs in the embedding space.

To adapt supervision across training regimes, we progressively increase the contribution of label-based positives using:

$$\alpha_t = \alpha_{\max} \frac{t}{T} \tag{4}$$

where t is the current epoch and T is the total number of epochs. Early training therefore behaves similarly to SimCLR, while later stages gradually incorporate stronger supervised structure.

ReACT generalizes several existing objectives: when $\alpha_t = 0$, it reduces to SimCLR; when $\alpha_t = 1$ and $\beta = \gamma = 0$, it reduces to SupCon; and fixed α_t values resemble hybrid contrastive objectives. Unlike these methods, ReACT dynamically adapts supervision according to representation reliability and cross-subject variability. The complete training procedure is provided in Algorithm 1 in Appendix A.

3. Experimental Setup

We evaluate contrastive learning methods on EEG representation learning under varying training regimes and cross-subject settings.

Datasets and Protocol. Experiments are conducted on two EEG motor-imagery benchmarks (details in Appendix B): **MMMI** and **BNCI2014-002**. MMMI provides a larger and noisier setting with substantial subject variability, while

BNCI2014-002 represents a smaller low-data benchmark. We use strict subject-wise splits to prevent subject leakage and evaluate performance across training-data fractions: $\{10\%, 25\%, 50\%, 75\%, 100\%\}$.

Compared Methods. We compare four approaches: SimCLR (Chen et al., 2020), SupCon (Khosla et al., 2020), a fixed Hybrid objective, and our proposed ReACT framework. All methods use identical experimental settings for fair comparison.

Model and Metrics. All methods share the same EEG encoder, optimizer, and training configuration. Weak augmentations consisting of additive noise and temporal masking are primarily used, while additional experiments evaluate stronger augmentations. Performance is measured using accuracy, macro-F1, weighted-F1, and MCC, with macro-F1 as the primary metric. Additional implementation details are provided in Appendix C.

4. Results and Discussion

4.1. Main Results

Table 1 presents the overall comparison between SimCLR, SupCon, Hybrid, and ReACT on MMMI and BNCI2014-002. On MMMI, ReACT achieves the best overall performance across all metrics, obtaining 94.7 Macro-F1 and 90.2 MCC, outperforming both fixed supervised and hybrid objectives. These results suggest that dynamically balancing instance-level and supervised positives improves robustness in large and noisy EEG settings. On BNCI2014-002, the performance differences are smaller. Hybrid achieves the highest Macro-F1 (54.8), while ReACT achieves the best MCC (25.6). The reduced gap across methods indicates that smaller datasets with stronger variability make supervised positive definitions less reliable. Overall, the results show that adaptive supervision provides the greatest benefit in larger and more heterogeneous training regimes.

4.2. Regime-Dependent Behavior

Figure 1 illustrates performance across varying training-data fractions, while full numerical results are provided in Appendix D. The results reveal a clear regime-dependent pattern. On MMMI, SimCLR remains relatively stable but saturates at lower performance levels, whereas SupCon improves substantially as more training data become available. In contrast, ReACT consistently achieves the strongest performance across all training fractions.

A similar trend is observed on BNCI2014-002. SimCLR performs competitively in smaller regimes, while supervised contrastive learning becomes more effective as training scale increases. However, both SimCLR and SupCon exhibit higher variability across fractions. ReACT provides more consistent behavior, particularly in intermediate and large-data settings, suggesting that adaptive weighting improves the reliability of supervised positives under strong cross-subject variability.

Overall, these findings support our central hypothesis that the usefulness of supervision in contrastive learning depends strongly on the training regime. Instance-level positives are more reliable in limited-data settings, whereas label-based supervision becomes increasingly effective once sufficient class coverage is available.

4.3. Ablation Study

Table 2 evaluates the contribution of each ReACT component. Removing the regime-adaptive schedule or subject-aware weighting substantially reduces performance, indicating that both adaptive supervision and cross-subject regularization are important for stable EEG representation learning. Similarly, removing representation-consistency weighting decreases performance, showing that reliability-aware positives contribute to robustness under noisy supervision. Overall, the full ReACT model consistently achieves the strongest performance, demonstrating that the combination of adaptive scheduling, subject-aware regularization, and representation-consistency weighting is necessary to obtain stable contrastive representations.

4.4. Stability Across Regimes

Table 3 measures performance stability across training fractions. SimCLR exhibits the lowest variance because its instance-based supervision remains relatively unchanged across regimes, although this stability comes with lower overall performance. SupCon shows substantially higher variance, reflecting the sensitivity of supervised positives to dataset scale and class coverage. ReACT achieves a more balanced trade-off between stability and performance. While slightly less stable than SimCLR, it significantly improves predictive performance while remaining more consistent than SupCon and Hybrid objectives. This indicates that adaptive supervision can reduce instability without sacrificing representation quality.

Overall, the results reveal that contrastive learning objectives should not be treated as universally optimal across all training conditions. Instead, their effectiveness depends strongly on data scale, supervision reliability, augmentation design, and cross-subject variability. SimCLR provides robust behavior in low-data settings because instance-level positives avoid noisy cross-sample supervision. In contrast, SupCon benefits from larger datasets where class coverage is sufficient to support reliable supervised grouping. Hybrid objectives partially balance these effects, but fixed weighting strategies remain limited because they cannot adapt to changing training conditions. ReACT addresses this limita-

Table 1. Main comparison of contrastive learning methods on EEG representation learning. Results are reported as mean ± standard deviation across folds/seeds.

Dataset	Method	Accuracy	Macro-F1	Weighted-F1	MCC
MMMI	SimCLR	63.0 ± 5.6	62.4 ± 5.8	62.4 ± 6.2	26.4 ± 11.2
MMMI	SupCon	90.4 ± 14.8	90.0 ± 15.2	90.2 ± 15.4	81.7 ± 28.0
MMMI	Hybrid	93.3 ± 5.9	93.3 ± 5.9	93.3 ± 6.0	87.2 ± 11.3
MMMI	**ReACT**	**94.8 ± 9.0**	**94.7 ± 9.1**	**94.8 ± 9.1**	**90.2 ± 17.0**
BNCI2014-002	SimCLR	60.6 ± 8.0	53.8 ± 12.7	53.8 ± 14.6	25.1 ± 15.8
BNCI2014-002	SupCon	58.4 ± 7.9	49.7 ± 13.2	49.5 ± 15.3	18.6 ± 18.7
BNCI2014-002	Hybrid	**61.2 ± 11.3**	**54.8 ± 16.1**	**54.8 ± 17.4**	24.2 ± 24.2
BNCI2014-002	**ReACT**	60.8 ± 9.9	53.0 ± 14.9	53.0 ± 17.0	**25.6 ± 17.7**

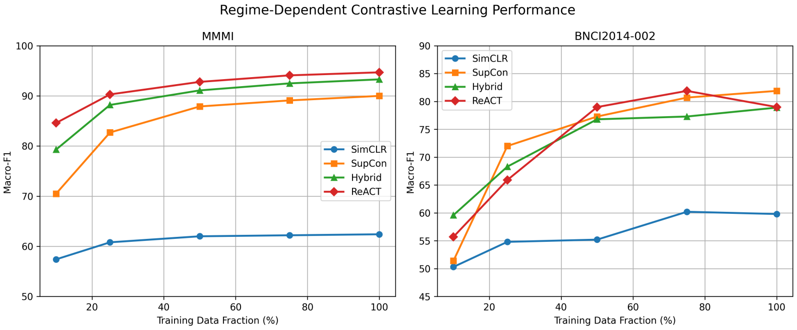

Figure 1. Regime-dependent contrastive learning performance across training-data fractions. SimCLR remains relatively stable in low-data regimes, whereas supervised contrastive learning improves substantially as training scale increases. ReACT provides consistently strong performance across both datasets and training regimes. (see Table in Appendix D)

Table 2. Ablation study of ReACT components. Results are reported using Macro-F1. BNCI2014-002 Results are reported using validation Macro-F1 from seed 0, fold 0 after 30 epochs.

Variant	MMMI	BNCI2014-002
ReACT without regime schedule	72.9	34.9
ReACT without subject weighting	70.0	33.8
ReACT without reliability weighting	79.6	33.5
Full ReACT	**95.6**	**33.8**

Table 3. Stability across training regimes on MMMI. Lower standard deviation across training fractions indicates more stable behavior.

Method	MMMI Std. Across Fractions
SimCLR	**2.10**
SupCon	7.57
Hybrid	5.63
ReACT	4.18

tion by dynamically balancing instance-level and supervised contrastive learning according to training regime and representation reliability. Across datasets and training fractions, ReACT consistently provides stronger or more stable performance, suggesting that adaptive supervision is particularly important for noisy physiological time-series domains such as EEG. These findings further indicate that conclusions drawn from small-scale contrastive learning experiments may not generalize to larger training regimes. More broadly, the results motivate future work on adaptive and uncertainty-aware contrastive objectives for clinical, multimodal, and high-variability time-series applications.

5. Conclusion

In this work, we showed that contrastive learning for multivariate EEG is strongly regime-dependent: instance-based objectives are more robust in low-data settings, whereas supervised contrastive learning becomes more effective as dataset scale and class diversity increase. These findings highlight a key limitation of existing methods, which assume fixed supervision reliability across training regimes. To address this, we introduced **ReACT** (Regime-Adaptive Contrastive Training), a framework that dynamically balances instance-level and label-based supervision through regime-adaptive scheduling, subject-aware weighting, and representation-consistency weighting. Experiments on EEG motor-imagery benchmarks demonstrate that ReACT provides more stable and consistent performance than SimCLR, SupCon, and fixed hybrid objectives across datasets and training regimes. Overall, our results emphasize the importance of adaptive supervision for robust contrastive learning in noisy time-series domains and motivate future work on uncertainty-aware and multimodal contrastive learning frameworks.

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A. ReACT: the algorithm

Algorithm 1 ReACT: Regime-Adaptive Contrastive Training

```
Require: Dataset $\mathcal{D} = \{(x_i, y_i, s_i)\}_{i=1}^{N}$, encoder $f_\theta$, temperature $\tau$
Require: Hyperparameters $\alpha_{\max}, \beta, \gamma$, total epochs $T$
for epoch $t = 1$ to $T$ do
    Sample mini-batch $\mathcal{B} = \{(x_i, y_i, s_i)\}_{i=1}^{B}$
    Generate augmented pairs:
        $x_i^1 = \text{Augment}(x_i), \quad x_i^2 = \text{Augment}(x_i)$
    Compute normalized embeddings:
        $z_i^1, z_i^2 = f_\theta(x_i^1), f_\theta(x_i^2), \quad z \leftarrow \frac{z}{\|z\|_2}$
    Compute regime coefficient:
        $\alpha_t = \alpha_{\max} \frac{t}{T}$
    Construct similarity matrix:
        $S_{ij} = \frac{z_i^\top z_j}{\tau}$
    for each anchor $i$ and sample $j \neq i$ do
        Compute reliability:
            $r_{ij} = \frac{z_i^\top z_j + 1}{2}$
        Compute adaptive weight:
            $w_{ij} = (1 - \alpha_t)\mathbb{1}_{\text{aug}}(i, j) + \alpha_t \mathbb{1}_{y_i = y_j} - \beta \mathbb{1}_{s_i = s_j} + \gamma r_{ij}$
        Clamp and normalize:
            $\tilde{w}_{ij} = \frac{\max(w_{ij}, 0)}{\sum_{k \neq i} \max(w_{ik}, 0)}$
    end for
    Compute batch loss:
        $\mathcal{L} = -\frac{1}{N} \sum_i \sum_{j \neq i} \tilde{w}_{ij} \log \frac{\exp(S_{ij})}{\sum_{k \neq i} \exp(S_{ik})}$
    Update encoder parameters $\theta$
end for
Trained encoder $f_\theta$
```

B. Table of Dataset Statistics

Table 4. Dataset statistics. The table reports the number of subjects, samples, channels, classes, sampling rate, and evaluation protocol used in our experiments.

Dataset	#Subjects	#Samples	#Channels	#Classes	Sampling Rate	Protocol
MMMI	109	∼1500	64	2	160 Hz	LOSO
BNCI2014-002	14	∼2240	15	2	512 Hz	LOSO

C. Table of Hyperparameters for Training

Table 5. Training hyperparameters used for all methods.

Hyperparameter	Value
Optimizer	AdamW
Learning rate	1×10^{-3}
Batch size	256
Epochs	100
Temperature τ	0.1
Embedding dimension	128
Hybrid weight λ	0.5
ReACT $\alpha_{\max}$	0.7
ReACT subject penalty β	0.05
ReACT reliability weighting	Progressive regime-adaptive weighting
Augmentation	Weak jitter + temporal masking
Gradient clipping	5.0
Weight decay	1×10^{-4}

D. Table: Regime-dependent Behavior

Table 6. Regime-dependent performance across training-data fractions. Macro-F1 is reported as mean ± standard deviation across completed folds/seeds for each dataset.

Dataset	Method	10%	25%	50%	75%	100%
MMMI	SimCLR	57.4 ± 6.9	60.8 ± 6.1	62.0 ± 5.8	62.2 ± 5.7	62.4 ± 5.8
MMMI	SupCon	70.5 ± 20.1	82.7 ± 18.4	87.9 ± 16.3	89.1 ± 15.7	90.0 ± 15.2
MMMI	Hybrid	79.3 ± 11.7	88.2 ± 8.4	91.1 ± 6.9	92.5 ± 6.2	93.3 ± 5.9
MMMI	**ReACT**	**84.6 ± 10.5**	**90.3 ± 9.7**	**92.8 ± 9.3**	**94.1 ± 9.1**	**94.7 ± 9.1**
BNCI2014-002	SimCLR	50.3 ± 17.7	54.8 ± 16.5	55.2 ± 14.3	60.2 ± 16.3	59.8 ± 13.1
BNCI2014-002	SupCon	51.4 ± 12.2	72.0 ± 24.5	77.3 ± 20.4	80.7 ± 17.8	81.9 ± 20.4
BNCI2014-002	Hybrid	59.6 ± 19.7	68.3 ± 22.6	76.8 ± 15.6	77.3 ± 19.8	78.9 ± 20.7
BNCI2014-002	**ReACT**	55.7 ± 20.6	65.9 ± 23.4	**79.0 ± 16.1**	**81.9 ± 12.8**	79.0 ± 22.6

E. Table: Pipeline Diagram for ReACT

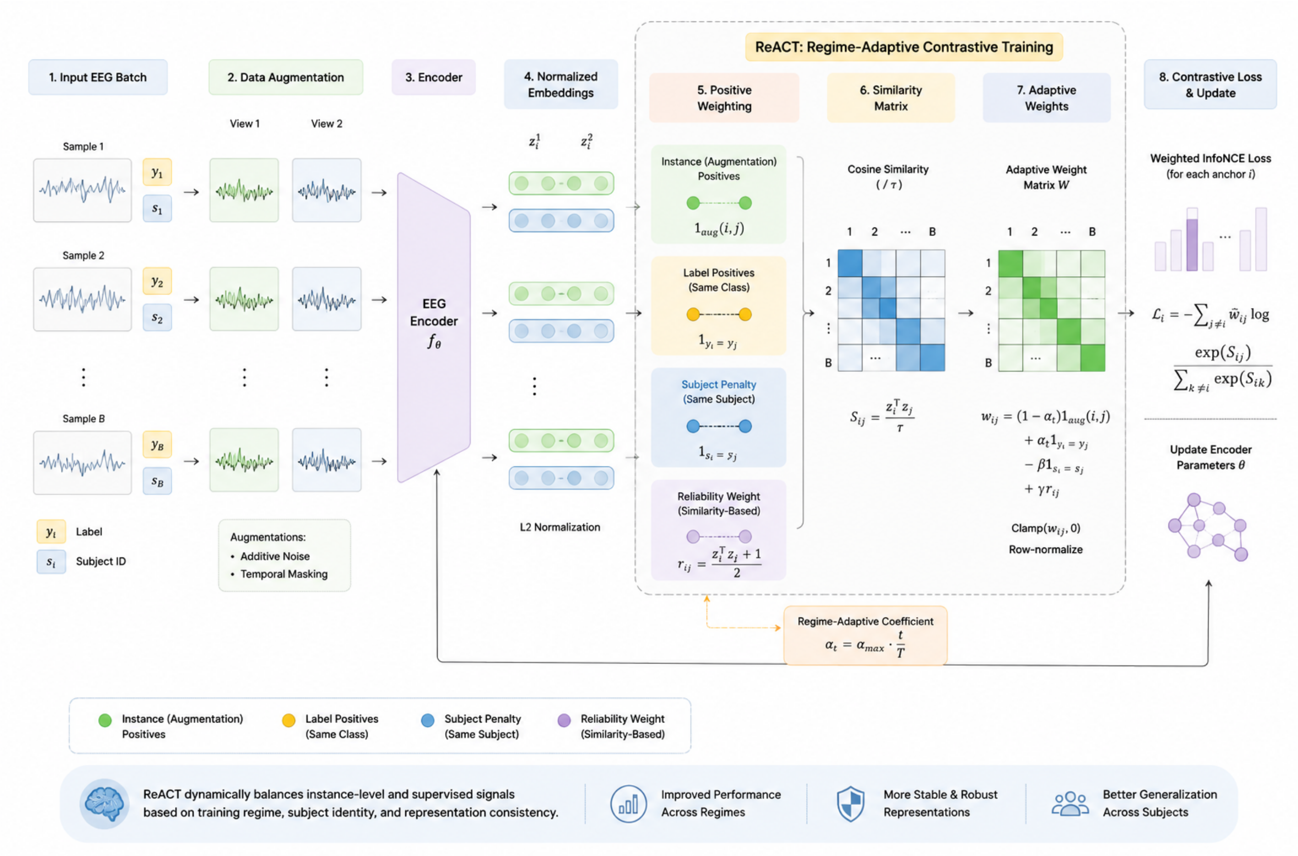

Figure 2. Overview of the proposed ReACT pipeline. EEG samples are augmented into multiple views and encoded into normalized representations. ReACT then constructs adaptive positive-pair weights using instance-level positives, label-based positives, subject-aware penalties, and representation-consistency weighting before optimizing the weighted contrastive objective.